Journal of Retailing and Consumer Services 69 (2022) 103089

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

The impact of COVID-19 on the evolution of online retail: The pandemic as a window of opportunity

Levente Szász[a,*], Csaba Bálint[b,a], Ottó Csíki[a], Bálint Zsolt Nagy[a], Béla-Gergely Rácz[a], Dénes Csala[c,a,d], Lloyd C. Harris[a,e]

[a] Faculty of Economics and Business Administration, Babeș-Bolyai University, 400591, Cluj-Napoca, Teodor Mihali str, 58-60, Romania
[b] National Bank of Romania, 030031, Bucharest, Lipscani str. 25, sector 3, Romania
[c] Department of Engineering, Lancaster University, Engineering Building, Lancaster University, Lancaster, LA1 4YW, United Kingdom
[d] Economics Observatory, School of Economics, University of Bristol, Beacon House, Queens Road, Bristol, BS8 1QU, United Kingdom
[e] Alliance Manchester Business School, University of Manchester, Booth St W, Manchester, M15 6PB, United Kingdom

ARTICLE INFO

Keywords:
Online retail
e-commerce
Multi-level perspective
Mobility
Government stringency

ABSTRACT

Pandemic-related shocks have induced an unexpected volatility into the evolution of online sales, making it difficult for retailers to cope with frequently occurring, drastic changes in demand. Relying on a socio-technical approach, the purpose of this paper is to (a) offer a deeper insight into the driving forces of online sales during the pandemic, and (b) investigate whether pandemic-related shocks accelerate the long-term growth of online retail. Novel, high-frequency data on GPS-based population mobility and government stringency is used to demonstrate how time spent in residential areas and governmental restrictions drive the monthly evolution of online sales in 23 countries. We deconstruct these effects into three main phases: lure-in, lock-in, and phase-out. Lastly, using time series analysis, we show that the pandemic has induced a level shift into the long-term growth trend of the online retail sector in the majority of countries investigated.

1. Introduction

The outbreak of the pandemic caused by the spread of a novel type of coronavirus, SARS-CoV-2, has induced an unprecedented shock to the global economy in terms of its speed and encompassing nature, having a significant impact on virtually all countries and economic sectors. During the pandemic, businesses and consumers have been forced continuously to adapt to the immediate and drastic changes brought about by this crisis. Furthermore, there is a general consensus that there will be long lasting global effects and the world economy will return to a "*new normal*" (Roggeveen and Sethuraman, 2020; Sneader and Singhal, 2021).

As with similar health-related and economic crises in the past, it is widely accepted that online retail represents a sector that plays a crucial role (Li et al., 2020; Guthrie et al., 2021), providing vital access for customers to essential products (Kirk and Rifkin, 2020; Martin-Neuninger and Ruby, 2020). Given its significant role, the present paper focuses on the evolution of online retail during the COVID-19 pandemic and analyses the short-term and potential long-lasting effects of this crisis.

Most of the existing papers studying the interaction between the early-stage of the pandemic and the online retail sector report that in several countries the outbreak of COVID-19 led to an unprecedented surge in online retail demand (e.g., Gao et al., 2020; Hobbs, 2020; Hwang et al., 2020). These observations are supported by commentators suggesting that in 2020 the "share of e-commerce in retail sales grew at two to five times the rate before COVID-19" (Lund et al., 2021). However, only a few studies acknowledge that, beyond the general upswing, the pandemic has increased the volatility of online sales evolution. Furthermore, literature offers little guidance on which factors can explain these changes in online sales during a crisis when traditional market mechanisms do not function as usual. In response, therefore, this paper aims to use large-scale, longitudinal data covering 23 different countries and multiple waves of the pandemic to investigate the *drivers of short-term online retail evolution during COVID-19*.

While some researchers have tentatively begun to explore these short-term effects (e.g., Chang and Meyerhoefer, 2021; Eger et al., 2021), the longer-lasting implications of the pandemic on the online

* Corresponding author.
E-mail addresses: levente.szasz@econ.ubbcluj.ro (L. Szász), Csaba.Balint@bnro.ro (C. Bálint), otto.csiki@econ.ubbcluj.ro (O. Csíki), balint.nagy@econ.ubbcluj.ro (B.Z. Nagy), bela.racz@econ.ubbcluj.ro (B.-G. Rácz), d.csala@lancaster.ac.uk (D. Csala), lloyd.harris@manchester.ac.uk (L.C. Harris).

https://doi.org/10.1016/j.jretconser.2022.103089
Received 29 May 2022; Received in revised form 21 July 2022; Accepted 23 July 2022
Available online 5 August 2022

retail sector have yet to be studied empirically. Most scholars emphasize the need to investigate whether the pandemic has truly altered the evolution trajectory of online retail or if the current crisis is merely a single shock after which the sector will return to its traditional evolutionary path as consumers and retail businesses return to their "old habits" in the post-pandemic period (Sheth, 2020; Eger et al., 2021; Reardon et al., 2021; Schleper et al., 2021). Consequently, given the uncertainty of what the "*new normal*" might bring for the online retail market, this paper also intends to use the most recent time series to investigate whether the *pandemic has altered the long-term evolution of the sector*.

In pursuing the two objectives (investigation of short-term drivers and long-term trend implications), this paper adopts Geels' (2002) multi-level perspective (MLP) as a theoretical lens to investigate technological transitions in a complex socio-technical context. We interpret the pandemic as a force capable of opening a "window of opportunity" (Dannenberg et al., 2020). Such windows constitute powerful tensions created at the level of the socio-technical landscape that bring a unique possibility for a technological novelty to break through and become more dominant in mass markets (Geels, 2004). Hence, we explore the interplay between the window of opportunity opened by COVID-19 and the growth of the online retail sector. More specifically, we aim to investigate (a) the short-term driving forces behind the exponential evolution of the online retail sector during the pandemic, and (b) whether the pandemic has truly created a window of opportunity for a positive shift in the long-term evolution of online retail. Along with pursuing these objectives we also aim to provide a theoretical contribution to the literature on windows of opportunity, a central concept that has received only limited attention in previous MLP studies (Geels, 2011; Dannenberg et al., 2020). In this regard, our paper aims to offer a more detailed insight into how a technological transition path might behave during such a period and to provide a means to evaluate the potential long-term effect of windows of opportunity.

2. Literature review

2.1. *The impact of COVID-19 on online retail*

Given the crucial role of online retail channels during a pandemic, researchers have examined a variety of ways in which COVID-19 has

Table 1
Summary of the literature on the impact of COVID-19 on the evolution of online retail.

Author(s)	Country (retail branch)	Period	COVID-19 implications	
			Short-term drivers	Long-term implications
Gao et al. (2020)	China (various sectors)	First wave (Feb 2020)	**Pandemic** (number of COVID-19 cases/day/city)[a]	–
Li et al. (2020)	China (food retail)	First wave (Feb 2020)	**Consumer behavior** (reduce health risks, gain access to food products)	–
Hao et al. (2020)	China (food retail)	First wave (Feb 2020)	**Consumer behavior** (food stockpile behavior associated with online channels; community-based ordering)	–
Guo et al. (2020)	China (food retail)	First wave	**Pandemic** (securing food supply for the urban population)	–
Jiang and Stylos (2021)	China (various sectors)	First wave (Feb–Mar 2020)	**Consumer behavior** (digital engagement during lockdowns)	
Tran (2021)	Vietnam (various sectors)	First wave (Jan–Mar 2020)	**Consumer behavior** (Fear of pandemic)	Depending on COVID-19 lifespan, consumer behavior might change in the long run.
Hall et al. (2021)	New Zealand (various sectors)	First wave (Feb–Mar 2020)	**Regulations** (travel restrictions and lockdown policies)	–
Martin-Neuninger and Ruby (2020)	New Zealand (grocery)	First wave (Feb–Apr, 2020)	**Regulations** (lockdown policies)	Negative online experience can have a long-term impact
Jílková and Králová (2021)	Czech Republic (various sectors)	First wave (Apr, 2020)	**Pandemic (**spread of COVID-19) **Regulations** (government restriction)	–
Mehrolia et al. (2021)	India (food retail)	First wave (Apr, 2020)	**Consumer behavior** (Fear for health)[a]	–
Hwang et al. (2020)	US (craft and art supplies)	First wave (until Apr, 2020)	**Regulations** (government-issued interventions)[a]	–
Chang and Meyerhoefer (2021)	Taiwan (food retail)	First wave (Jan–Apr, 2020)	**Pandemic** (number of new infections)[a] **Consumer behavior** (media consumption)[a]	Customers trying the online channel for the first time might continue using this channel
Beckers et al. (2021)	Belgium (various sectors)	First wave (Apr–Jun 2020)	**Regulations** (travel restrictions, social distancing rules)	The ad-hoc setup of local online retail channels threatens their post-covid sustainability
Guthrie et al. (2021)	France (para-pharmaceutical, healthcare, well-being and beauty)	First wave (until Jul 2020)	**Consumer behavior** (panic buying, coping with and adapting to the pandemic context)	–
Hobbs (2020)	Canada (food retail)	First wave	**Consumer behavior** (panic buying) **Regulations** (stay-at-home and distancing orders)	Online food retail will receive a sustained upward shift in adoption
Kirk and Rifkin (2020)	US (various sectors)	First wave	**Regulations** (social distancing rules)	–
Pantano et al. (2020)	n.a. (various sectors)	First wave	**Regulations** (lower accessibility of stores) **Consumer behavior** (health concerns)	Further store closures or bankruptcy of major brick and mortar retailers
Reardon et al. (2021)	Asia and Latin America (food retail)	First wave	**Regulations** (lockdown policies)	–
Sheth (2020)	n.a.	First wave	**Consumer behavior** (impact of a disaster and crisis on shopping behavior)	–
Eger et al. (2021)	Czech Republic (various sectors)	Second wave (Sep 2020)	**Consumer behavior** (fear for health)[a]	Customers might change their shopping habits in the long run
Chopdar et al. (2022)	India (mobile shopping)	Second wave (Sep–Dec 2020)	**Consumer behavior** (fear of Covid-19)[a]	–

[a] Offers large-scale empirical evidence for the hypothesized driver(s) on online sales.

influenced online shopping. As COVID-19 was first identified in China, initial studies investigated how the outbreak of the crisis has reshaped the retail landscape in China with emphasis on the increasing importance of online channels (Gao et al., 2020; Guo et al., 2020; Hao et al., 2020; Li et al., 2020; Jiang and Stylos, 2021). These studies focused on how the outbreak of the pandemic influenced online shopping (Gao et al., 2020; Guo et al., 2020), and how online channels helped the population to cope with the emerging health-crisis (Li et al., 2020; Hao et al., 2020).

Given the narrow focus of initial studies, authors called for further research in other countries better to understand the global impact of the pandemic on online retail (Gao et al., 2020; Li et al., 2020; Jiang and Stylos, 2021). Subsequent studies taking this research avenue offered a good cross-section globally by covering multiple different countries but investigated almost exclusively the short-term impacts of COVID-19 on online retail, using data from the first wave of the pandemic (Table 1). Moreover, observers typically argued that the major driving forces behind the exponential proliferation of online channel use in the context of COVID-19, can be grouped in two distinct, but intertwined categories: (a) governmental regulations and restrictions, and (b) pandemic-induced changes in customer behavior. In line with this observation, Shankar et al. (2021) also contend that *"many shoppers move a large portion of their business online during the COVID-19 outbreak either by* ***choice*** *or due to* ***regulation*** *…"*. Therefore, the next two subsections review the studies that attribute the changes in online sales to one of these two factors.

2.1.1. Studies highlighting the impact of changing customer behavior

Adopting a behavioral perspective, Chang and Meyerhoefer (2021) illustrated how the first wave in Taiwan (where no strict stay-at-home orders or business closures were imposed) has shifted consumers' attention towards online channels. In the early weeks of the pandemic the surge in the number of confirmed cases increased both sales and the number of customers of online food commerce. The change in customer behavior was also induced by the media, as COVID-19 related press articles and Google searches also positively correlated with online food sales.

In a similar manner, Sheth (2020) argued that the pandemic had several powerful and immediate effects on consumer behavior: while facing constraints, consumers improvised and replaced old habits with new ones, such as switching to online retail channels, enabling thereby the "store to come home". In line with this, Jiang and Stylos (2021) proposed that individual pressures during lockdowns force consumers to create a "new retail purchasing normality" involving higher digital engagement and increased online purchases. Consultancy papers also supported this view. A multi-country survey conducted by McKinsey & Company demonstrated that the pandemic induced a major shift in consumer behavior, at least two thirds of customers having tried new, mostly online forms of shopping (Sneader and Singhal, 2021).

In terms of shifting consumer behavior, Tran (2021) proposed that fear of the pandemic can also drive online purchasing intentions aiming to improve the health safety of the consumer and the surrounding community. Researchers focusing on the second wave of the pandemic (Chopdar et al., 2022; Eger et al., 2021) also connected the fear of the virus to increased online shopping. One exception is identified by Mehrolia et al. (2021), concluding that a considerable majority of Indian customers decided not to order food through online channels during the first wave of the pandemic due to the fear connected to food delivery.

Hao et al. (2020) focused on a different aspect of customer behavior. Their study points out that panic buying (i.e., ordering more than the short-term necessity of the household due to fear), which is a common consumer response during disasters, is more associated with online food retail channels than with traditional channels. Following this idea, Guthrie et al. (2021) use the react-cope-adapt model (Kirk and Rifkin, 2020) to illustrate that during the first month of the pandemic in France consumers reacted by panic buying, dramatically increasing the online purchasing of essential products. This period was followed by coping with the crisis which led to an increase of online orders related to non-essential products. The adapt phase was supposed to show a sustained modification of online purchasing behavior. However, due to limited data available, the authors concluded that long-term behavior changes require further investigation.

2.1.2. Studies highlighting the impact of government regulations

During the pandemic, several governmental restrictions had an immediate impact on online retail. For example, Martin-Neuninger and Ruby (2020) and Hall et al. (2021) identify government-related factors, namely the lockdown period and travel restrictions, as primary reasons behind the surge in online shopping in New Zealand. Hobbs (2020) also argued that initial stay-at-home and distancing orders issued in Canada led to an uptake of the online food retail: while online grocery deliveries were already used by early adopters in the pre-pandemic era, during the outbreak many late-adopter customers tried this channel for the first time. Jílková and Králová (2021) reported similar phenomena in the Czech Republic for all generational cohorts. In summary, unexpected regulations imposed by governments determined an immediate increase in demand for online shopping: existing customers started to use online channels more frequently, while new customers, including older and less tech-savvy generations, turned to online channels for the first time (Hwang et al., 2020; Pantano et al., 2020).

From the retailer's perspective, Reardon et al. (2021) provided several case examples of Asian and Latin American food industry firms strengthening their e-commerce business models or reconfiguring their entire food supply chains as a response to early-stage lockdown policies. Based on a survey among small Belgian retailers, Beckers et al. (2021) found that restrictions have doubled online orders during the first wave of the pandemic. To match the increase in demand, half of the retailers not using online channels before the pandemic opened one during the first months of COVID-19. Based on a literature review, Kirk and Rifkin (2020) also predicted that in order to conform to social distancing regulations, online retail coupled with contactless distribution methods would substantially gain ground during the pandemic. However, results related to the long-lasting effects of the pandemic on online retail are still "speculative in nature" (Hobbs, 2020). Many of the customers who made the shift due to the restrictions might continue to utilize online channels in the long run. Other customers might return to traditional channels as soon as possible (Beckers et al., 2021; Mehrolia et al., 2021). Thus, whether online retail can capitalize on the pandemic in the long run is still a subject of debate.

2.1.3. Summary and research questions

A summary of the key studies is provided in Table 1 in chronological order, highlighting the short-term drivers (i.e., government regulations and/or customer behavior, beside the papers narrowly focusing on the effect of the pandemic itself) and potential long-term implications related to the growth of the online retail sector.

Based on the literature, we derive two main conclusions that serve as basis for our research questions. First, as demonstrated in Table 1, there is a plethora of mostly anecdotal, non-empirically-based evidence that during the pandemic (and beside the pandemic itself) two major factors, i.e., government restrictions and consumer behavior changes, drove a significant initial surge in online shopping. Second, extant studies failed to offer insights into *how* these factors drive online sales during the *entire* period of the current pandemic (Schleper et al., 2021). Therefore, we cover the full period of COVID-19 to date and provide more conclusive empirical evidence on how these two factors influence the evolution of online retail.

RQ1. How do changes in customer behavior and government regulations drive the evolution of online retail during the pandemic?

Moreover, the long-term implications of this change in online retail use have remained, so far, a subject of anecdotal speculation (Table 1). However, changes to the retail sector might become a constant in the "*new normal*", and further research is needed "to understand the short-term and long-term impact of the pandemic on consumer behavior and provide guidance on how retailers should cope with those changes" (Roggeveen and Sethuraman, 2020). Hobbs (2020) suggested that COVID-19 prompted sceptics and late-adopters to use online retail channels, and these new customers are likely to continue to shop online even after the pandemic. More cautious voices, however, asked the question whether the pandemic has "swung the pendulum too far and too fast towards online shopping" (Gauri et al., 2021), which may potentially result in an unsustainable boost to online retail. Thus, the extent to which this shift will lead to a fundamental leap in the long-term role of online retailing is unknown.

RQ2. What trend-shifting impact does the pandemic have on the long-term evolution of online retail?

In answering RQ1 and RQ2 we also aim to extend the scope of existing research (Table 1) in four different aspects. Given that COVID-19 is a global phenomenon, we aim to cover a larger geographical region compared to the majority of previous studies focusing on a single country. Second, in contrast with existing research mostly investigating a single branch of the online retail sector, we propose to analyze the online retail sector as a whole, covering the sales of all types of products. Third, we integrate novel measures into the analysis that have emerged during this pandemic (mobility indicators, government stringency index) to be able better to explain the evolution of the online retail sector during this crisis. Fourth, we investigate a longer period before and during the pandemic than previous studies to infer long-term implications.

2.2. A socio-technical approach to study the evolution of online retail during COVID-19

The multi-level perspective (MLP) has been established as insightful in studying COVID-19 related developments in the online retail sector (Dannenberg et al., 2020). Consequently, we use the MLP as a theoretical lens to study the short and long-term evolution of online retail. Geels (2002) argues that the central tenet of MLP is that technological transitions are not only dependent on the development of the technology itself, but also pivot on the broader socio-technical context. In line with this view, technological transition represents a change from one socio-technical configuration (regime) to other: beyond the substitution of an older technology with a newer one, such transitions include changes in other socio-technical dimensions such as infrastructures, policies, user practices, and markets (Geels, 2002, 2004).

According to the MLP, technological transitions are shaped by the interaction between developments unfolding on three analytical levels (Geels, 2002, 2004, 2011):

- *Technological niches* represent the micro-level of the MLP. Niches are quasi-protected spaces where radical innovations are developed (e.g., R&D laboratories, subsidized development projects, or specific user categories supporting emerging innovations). They are unstable socio-technical configurations where innovations are carried out by a limited number of actors. Processes in the niche are gradually linked together and stabilize in time into a dominant design that allows for the radical innovation to break through to the next level.
- *Socio-technical regimes* represent the meso-level of the MLP. Regimes refer to "the semi-coherent set of rules that orient and coordinate the activities of social groups" (Geels, 2011) creating thereby a "deep structure" that ensures the stability of the current socio-technical system. Nevertheless, the semi-coherence of these rules allows for a dynamic stability which enables further incremental innovation, with small adjustments accumulating into stable technological transition paths. A socio-technical regime is formed by the co-evolution of different sub-regimes, each with its own set of rules and dynamics: user and market, technological, science, policy, and socio-cultural sub-regimes. According to Geels (2004), the socio-technical regime can be understood as the meta-coordination of the different sub-regimes that determines technology adoption and use.
- The *socio-technical landscape* represents the macro-level of the MLP. The landscape provides a wider, technology-external context for the interactions of actors within the niche and the socio-technical regime. Actors cannot influence elements of the landscape on the short-run, and changes at the landscape level take place usually slowly, representing longer-term, deep structural tendencies (e.g., macroeconomic processes, cultural patterns, political trends).

An important implication of the MLP is that the future evolution of a (new) technology does not only depend on the processes within the niche, but also on the interactions between different levels; including the regime and landscape levels. Geels and Schot (2007) contend that the general pattern of technology transition involves all three levels: (1) niche innovations align and gain internal momentum, (2) landscape developments put pressure on existing regimes, and (3) regimes destabilize creating an opportunity for niche innovations to break through to mass markets.

In terms of the interplay between COVID-19 and online retailing, another important concept linked to the MLP is the "window of opportunity". Geels (2002) argues that windows of opportunity are created when tensions appear in the current socio-technical regime or when landscape developments put a pressure on the current regime for internal restructuring. These tensions loosen the rules of the socio-technical regime and create opportunities for technologies to escape the niche-level and become more deeply embedded in the regime. Competition with the existing technology becomes more intensive, triggering wider changes in the regime, where the new technology may replace the old one in the long run (Geels, 2004).

Dannenberg et al. (2020) conclude that COVID-19 represents a critical landscape development that puts pressure on the socio-technical configuration of the retail sector. In line with our literature review, they suggest that two sub-regimes were particularly affected: policy regime (government regulations) and, user and market regime (sudden change in customer behavior). The authors further argue that these two major changes have opened a window of opportunity for online grocery retail to gain substantial market share. In this regard, RQ1 aims to investigate how the developments within these two dimensions influence the evolution of the online retail sector during the opening up of a window of opportunity (Fig. 1). Given that, to date, the MLP offers little insight into the evolution of a technology during a window of opportunity (Dannenberg et al., 2020), answering RQ1 should enrich this theoretical framework by explicating the forces that drive technology transitions *during* tensions in the landscape and the socio-technical regime (i.e., during a window of opportunity).

Concerning the long-term impact of this window of opportunity, we investigate whether it enables the online retail sector to gain a significantly higher share of the whole retail sector on the long run (technology trajectory in Fig. 1) to the detriment of offline channels (Helm et al., 2020). However, in the long run, MLP is not necessarily about mapping "winning" technologies that entirely replace/reconfigure existing regimes: it is just as possible that the breakthrough of a new technology will lead to a symbiosis with incumbent socio-technical regimes (Geels, 2002; Genus and Coles, 2008). Thus, in our case, the question is more about the relative share of online retail and physical retail within the retail sector (cf. omnichannel retailing, Gauri et al., 2021). Beside speculation, current literature offers little guidance in this regard. Dannenberg et al. (2020) suggest that even if the pandemic has led to an upswing of online shopping, there is no indication for a fundamental long-term shift from physical to online retail. The authors, however, base their assumptions on a limited set of data, both from a temporal (March–May 2020) and from a geographical/sectoral perspective (German grocery retail). On the other hand, many other authors advocate a breakthrough of online retail as a result of taking advantage of the

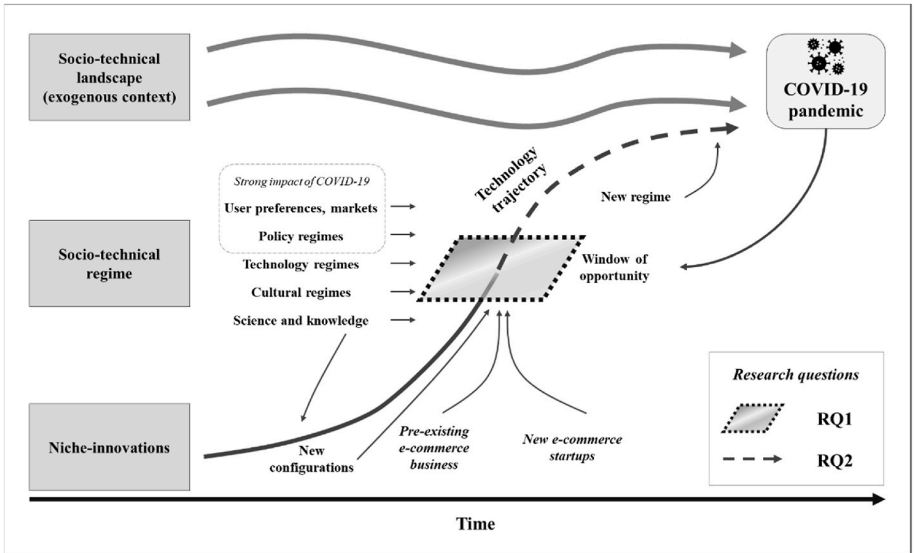

Fig. 1. COVID-19 and the trajectory of online retail evolution (adapted from: Geels, 2002; Dannenberg et al., 2020).

window of opportunity created by the pandemic (e.g., Chang and Meyerhoefer, 2021; Hobbs, 2020; Tran, 2021). Answering RQ2 is designed to explicate and illuminate further this debate.

3. Data and variables

3.1. Data used in short-term analysis (RQ1)

To investigate RQ1, we use as *dependent variable* the monthly evolution of online retail sales during the pandemic (Feb 2020–Jan 2022) in European countries. We rely on Beckers et al. (2021) who define online retail channel use as the selling of goods via mail, phone, website, or

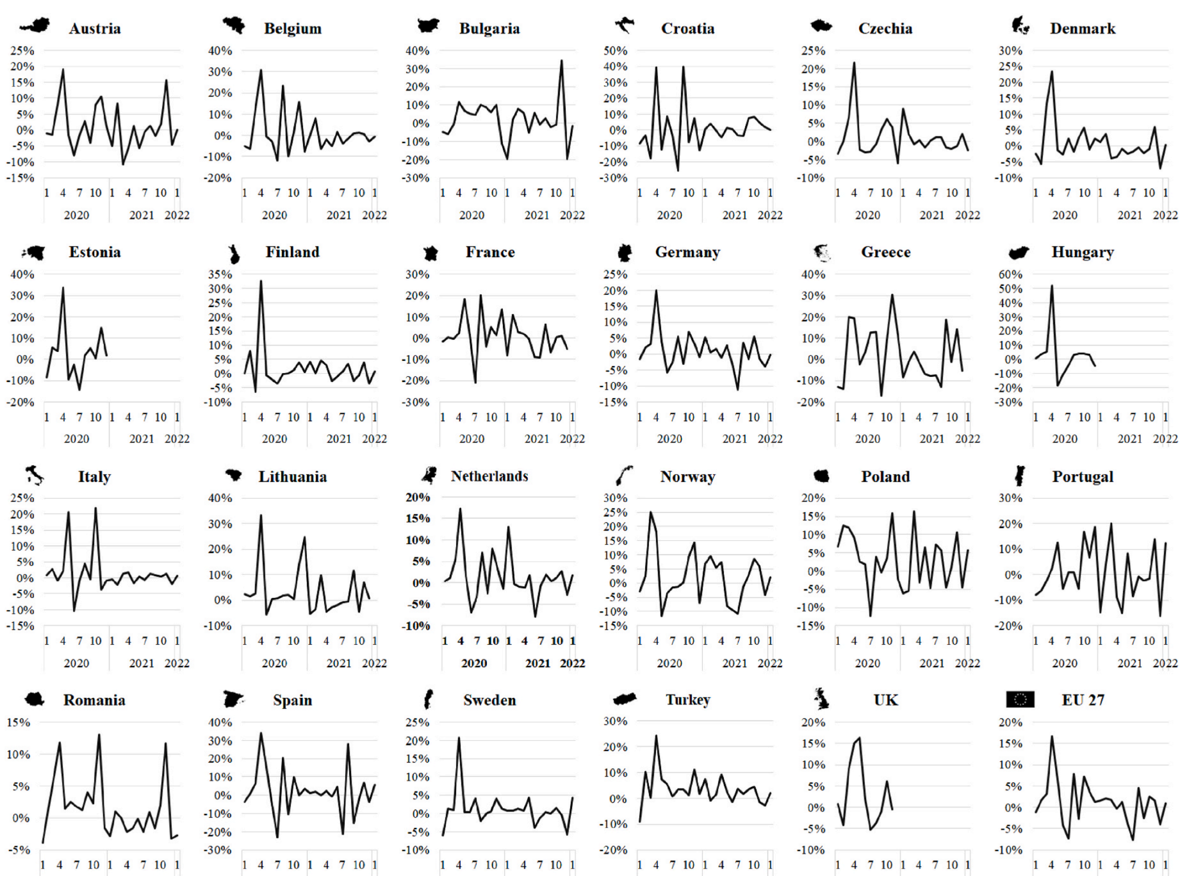

Fig. 2. Monthly changes in online retail turnover during the pandemic in the countries investigated.

social media. Therefore, we adopt NACE-level retail trade data published by Eurostat using the index of deflated turnover (i.e., turnover in real terms, 2015 = 100) for the "Retail sale via mail order houses or via Internet" sector. Seasonally and calendar adjusted time series data is used to assess the monthly changes during the pandemic in this sector, shortly denoted from now on "online retail" (*ΔOnline_retail*). In terms of countries, the Eurostat database was deemed the most suitable to study our research questions as it provides online retail data for 23 European countries (20 countries of the European Union, plus Norway, UK, and Turkey, covering thereby all major economies from Europe). This sample offers a rich variety of pandemic-related contexts: each of these countries was hit by the pandemic to a different extent and the reaction of authorities was also fairly diverse (Hale et al., 2021). Fig. 2 illustrates the evolution of the *ΔOnline_retail* variable in these countries.

To investigate this volatile evolution, two novel measures are used as *explanatory variables* that have been introduced recently as a response to the need to track social phenomena more frequently and more precisely during the pandemic.

The first variable is a proxy of changes in general customer behavior: *population mobility*. Shankar et al. (2021) argue that during a period characterized by dramatic and frequent changes in shopping behaviors, high-frequency, mobile GPS data can offer better information for retailers. Therefore, we integrate into our analysis the mobility data provided by Google® through their Community Mobility Reports (Google, 2021), comprising several types of mobilities grouped by the destination/location of the mobility. Based on Beckers et al. (2021) who argue that COVID-19 has temporarily put an end to hypermobility cutting short consumers' physical range around their homes, we select the residential component (*ΔResidential*) from the different forms of mobility, arguing that the changes in residential mobility (i.e., amount of time spent at home) could be the strongest component to explain changes in online shopping. Given that there might be some time needed for online shopping behavior to adjust to changes in mobility, the one-month lagged version of the variable is also used in our model (*ΔResidential(-1)*).

The second explanatory variable incorporated in our analysis is related to *government restrictions*. We use data from the Oxford COVID-19 Government Response Tracker, more precisely the values of the COVID-19 Stringency Index which aggregates the stringency of lockdown-type governmental measures, such as school closures, travel restrictions, bans on public gatherings, workplace closures, etc. (Hale et al., 2021). This represents the most suitable proxy to measure the type of regulations connected by previous literature to online channel use during the pandemic (Table 1). The index provides a multi-country panel of daily frequency, measured as a percentage value; 100% representing the highest level of stringency. To match the frequency of the dependent variable, the monthly change of the index is computed as explanatory variable (*ΔGovernment_stringency*). The one-month lagged variant is also introduced in the analysis (*ΔGovernment_stringency(-1)*).

Beside the two novel explanatory variables generated during the pandemic, we integrate several *control variables* in our analysis. These variables assess the income and purchasing power of the population (GDP/capita and unemployment level in each country), the level of urbanization (density of the population in each country), the level of education (percentage of the population attending tertiary education), the pervasiveness of online channels (Internet penetration), and the actual pervasiveness of online shopping (Online retail share in the retail sector) (Hortaçsu and Syverson, 2015). Data for all countries analyzed are retrieved from the Eurostat database. The unemployment variable has a monthly frequency (*Δ Unemployment*), while the other variables (*GDP/capita, Internet penetration, Tertiary education, Population density, Online retail share*) change on a yearly basis. Descriptive statistics for the monthly variables are provided in Table 2. The correlation matrix is included in Appendix A.

3.2. Data used in long-term analysis (RQ2)

To evaluate the trend-shifting potential of the pandemic in the online retail sector, the same retail trade data is used as for the short-term analysis, covering however a longer period of time between Jan 2000 and Jan 2022 (*Online_Retail*). To offer an overview of the long-term evolution of our focal variable, we present a boxplot containing data for all countries aggregated to annual averages, normalized on a 0–100 scale (Fig. 3, left). Primary visual inspection suggests that two periods can be distinguished in terms of the dynamism of the sector (2000–2010 characterized by slower growth pace versus 2011–2021 showing stronger momentum), while the relatively higher values of the last two boxplots indicate that it is beneficial to investigate whether the pandemic has induced a level shift into the evolution of online retail.

Furthermore, to assess whether the online retail sector could exploit the window of opportunity opened by the pandemic, we compute another variable as a proxy measuring the share of online retail in total retail sales. For this purpose, we calculate the ratio between the indices of deflated turnover of online retail and the "Retail trade, except of motor vehicles and motorcycles" sector, this latter being a proxy for total retail sales (*Online_Retail_Ratio ≈ Online_Retail/Total_Retail*) (Fig. 3, right). The ratio approach is also consistent with theory (symbiotic technologies: Geels, 2002) and previous research (Hortaçsu and Syverson, 2015).

4. Analysis and results

4.1. Short-term analysis (RQ1)

4.1.1. Panel regression analysis

To illuminate the impact of mobility and government restrictions on the monthly evolution of online sales, we have elected to implement a panel regression model. We have performed three random-effects and three cross-section fixed-effects panel regressions. We opted for the panel specification because it enables us to harness the rich structure of our data and to account for the unobserved heterogeneity present in the data. We perform 2 × 3 = 6 regressions because of the different methodology (fixed vs. random effects), and the 3 combinations resulting from including only the government stringency variables, only the residential mobility variables, and both. Five control variables were nearly collinear in the fixed effects case; therefore Table 3 presents only the estimates for these variables in the random effects case. Our main specification is the following:

$$\begin{aligned}\Delta Online\ retail_{ti} = \alpha + \sum_{j=1}^{10}\beta(C)_j C_{ijt} = \alpha + \beta_1 \Delta Unemployment_{ti} \\ + \beta_2 \Delta Residential_{ti} \\ + \beta_3 \Delta Residential(t-1)_{ti} \\ + \beta_4 \Delta Stringency_{ti} \\ + \beta_5 \Delta Stringency(t-1)_{ti} \\ + \boldsymbol{\beta_{controls}} \boldsymbol{\Delta Controls_{ti}} + \varepsilon_{ti}\end{aligned}$$

where C_{ijt} and $\beta(C)_j$ are the independent variables and their coefficients, i is the index of countries, t of time, and j of the equation variables.

Results of the fixed effects specifications of our panel regression model (equations 1 to 3) indicate that our first variable of interest, residential mobility, and its one-period lag, have a significant impact on the monthly change in online retail sales, both variables having the expected positive sign. The same can be pointed out for the government stringency and lag variables. However, when we include both residential mobility and government stringency, only the first remains significant, due to high collinearity between the two explanatory variables. The results are similar in the random effects case (equations 4 to 6). The goodness-of-fit statistics (adjusted R-squared, F-statistic) are quite high

Table 2
Descriptive statistics of the main variables included in the short-term analysis.

	Variables					
Statistics	Δ Online retail	Δ Unemployment	Δ Residential	Δ Residential (−1)	Δ Government stringency	Δ Government stringency (−1)
Mean	0.0206	−0.0132	0.0039	0.0035	2.1595	2.1232
Median	0.0087	−0.1000	0.0027	0.0021	0.0000	0.0000
Maximum	0.5520	1.5000	0.2071	0.2071	58.0242	58.0242
Minimum	−0.2554	−2.0000	−0.1321	−0.1321	−31.4557	−31.4557
Std. Dev.	0.0904	0.4170	0.0419	0.0426	13.5469	13.7702
Skewness	1.1902	0.1672	0.7464	0.7609	1.37032	1.36048
Kurtosis	7.1846	6.1327	5.3353	5.2217	5.8321	5.70269
No. of Observations	507	509	552	529	552	529

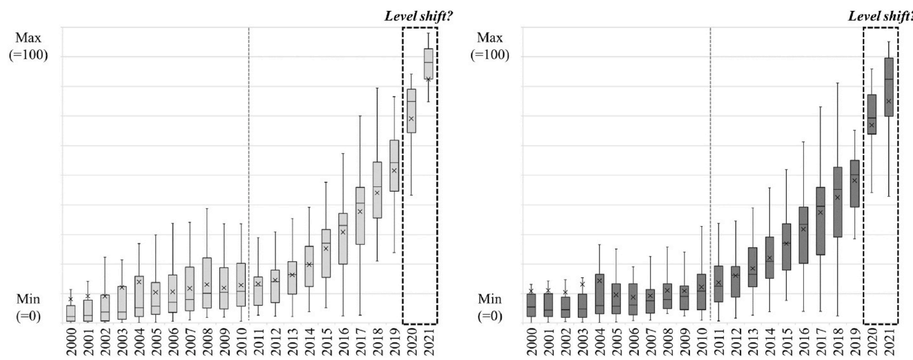

Fig. 3. Long-term evolution of online retail turnover (left) and online retail market share (right) in the countries investigated (normalized: min = 0, max = 100).

Table 3
Regression models.

	Dependent variable: Δ Online retail					
	1	2	3	4	5	6
	Fixed effects (FE)			Random effects (RE)		
GDP/capita	–	–	–	−0.000000 (−0.64)	−0.000000 (−0.39)	−0.000000 (−0.61)
Internet penetration	–	–	–	−0.000656 (−0.47)	−0.000546 (−0.39)	−0.000554 (−0.40)
Tertiary education	–	–	–	−0.000405 (−1.30)	−0.000485 (−1.55)	0.000428 (−1.38)
Population density	–	–	–	0.028760 (1.04)	0.031739 (1.15)	0.028319 (1.03)
Online retail share	–	–	–	−0.000011 (−0.01)	0.000033 (0.04)	−0.000011 (−0.01)
Δ Unemployment	0.010779 (1.65)	0.001487 (0.15)	0.008275 (0.84)	0.007104 (0.61)	−0.007929 (−0.67)	−0.001937 (−0.16)
Δ Residential	**0.530978 (5.56)****		**0.336457 (2.06)***	**0.632360 (5.38)****		**0.502955 (2.48)***
Δ Residential (-1)	**0.580693 (6.05)****		0.283552 (1.72)	**0.666569 (5.48)****		0.228287 (1.10)
Δ Government stringency		**0.001803 (5.93)****	0.000801 (1.52)		**0.001991 (5.77)****	0.000615 (1.01)
Δ Government stringency (-1)		**0.001671 (5.39)****	0.001006 (1.94)		**0.001796 (4.99)****	**0.001408 (2.36)***
R^2	0.204	0.202	0.217	0.220	0.219	0.237
Adjusted R^2	0.160	0.158	0.169	0.203	0.202	0.216
F-statistic	4.60	4.55	4.57	12.91	12.78	11.28
No. of observations	456	456	456	374	374	374

Notes: t-values in parentheses; *significant at 0.05; **significant at 0.01.

for panel regressions, indicating that the explanatory variables introduced in the panel explain a large proportion of the variation of the monthly change in online retail sales.

Thus, results altogether indicate that both residential mobility and government stringency are significant predictors of online retail channel use: as residential mobility increases (i.e., people spend more time at home) and, alternatively, as government stringency increases (i.e., anti-COVID-19 measures become stricter) the use of online retail channels increases. Furthermore, the impact of all control variables is insignificant, meaning that mobility and government stringency indicators provide a better explanation for the variation of online retail sales during the pandemic than traditional variables that have been used to explain the evolution of the online retail sector in pre-pandemic periods.

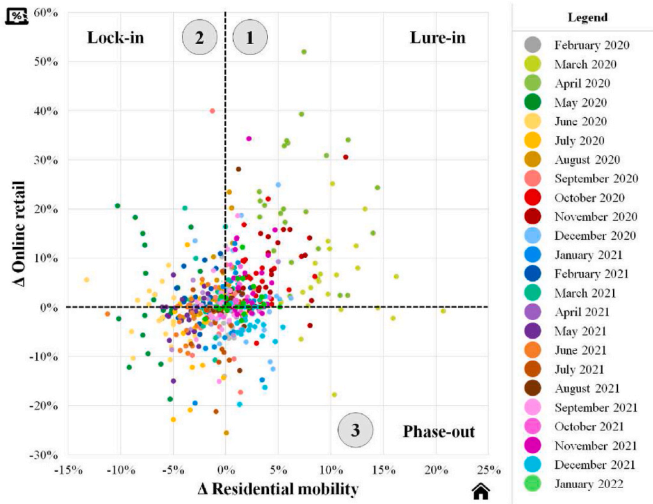

Fig. 4. Monthly evolution of online sales and residential mobility during the pandemic in the countries investigated.

4.1.2. *Detailed analysis of short-term effects*

While panel regression results show that both residential mobility and government stringency are good predictors of the evolution of online sales, relationships between variables are rarely perfectly linear. Therefore, we provide a more detailed analysis on the interplay between these variables. Fig. 4 illustrates the monthly evolution of online sales (vertical axis) together with the monthly percentage change in residential mobility (horizontal axis) for the entire period of the pandemic, each dot representing one country in one month.

Beside the general positive relationship between the two variables, the scatter plot also indicates that three different forces can be identified that shape the evolution of online retail sales during the pandemic. First, there are periods in which mobility is restricted more and more to residential areas, and consumers adapt by significantly increasing their monthly spending on online retail channels (as high as +30–50% during the first wave of the pandemic). This process is exactly what was expected during the pandemic: as the mobility range of people is restricted primarily to their homes, they turn to online retail channels more frequently. This process is termed the **"lure-in"** phase. Typical months during which the lure-in phase was dominant were Mar 2020, Apr 2020, Oct–Nov 2020, Nov 2021, and Jan 2022 (Fig. 5).

However, it is also observable that when consumers are not confined to residential areas and start increasing their mobility outside their homes (i.e., residential mobility decreases), a decrease in online spending does not follow automatically, as people tend to continue to use, or even increase the usage of, online retail channels. Additionally, in many cases a large drop in residential mobility is paired with no significant change in online retail sales. These cases are labelled as the **"lock-in"** phase, which means that temporarily consumers remain users of online channels even if their mobility would allow them to use offline channels more intensively. Thus, mobility restrictions have an immediate (lure-in), but also a lagged (lock-in) impact on online retail channel use, in line with the significance of lagged variables in our panel regression model (Table 3). The most typical months in which several European countries went through this lock-in phase were May 2020, Jun 2020, Feb 2021, Mar 2021 (Fig. 5). This phase is not as consistent on a monthly basis as the lure-in phase, several countries experiencing a negative change in online channel use, concurrently with the decrease of residential mobility.

Lastly, there is also a **"phase-out" period** denoting cases where online retail use decreases, while time spent at home generally decreases. During these months a part of the former online shopping volume of customers is most probably replaced by (or allocated back to) offline channels. Furthermore, in some rare instances residential mobility has a slight increase, while consumers still decrease their online spending. Predominantly phase-out months include Jul 2020, May–Jul 2021, Dec 2021 (Fig. 5).

The same three phases can be observed if the residential mobility indicator on the vertical axis is replaced by the government stringency index (Figs. 6 and 7). In summary, there is a clear lure-in phase which was noticeable especially during the beginning of the first and second wave of the pandemic (Mar–Apr, 2020; Oct–Nov 2020): sudden drops in mobility and severe governmental restrictions clearly prompt customers to shop online. This effect has some "stickiness" (lock-in phase) because as governmental restrictions are eased, certain customers continue to use (or even increase the use of) online retail channels. Nevertheless, after a relatively short period the lock-in effect fades and customers drop their online shopping volume significantly (phase-out), countervailing

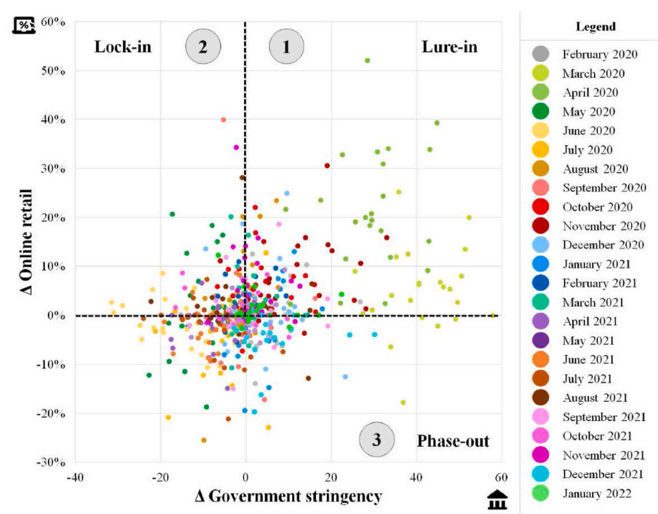

Fig. 6. Monthly evolution of online sales and government stringency during the pandemic in the countries investigated.

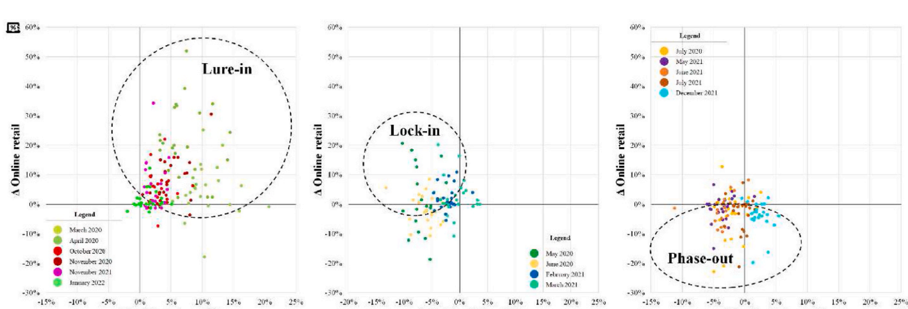

Fig. 5. Monthly evolution of online sales and residential mobility during different phases of the pandemic in the countries investigated.

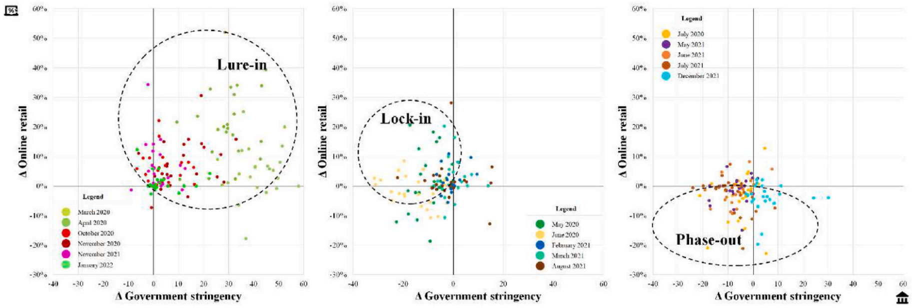

Fig. 7. Monthly evolution of online sales and government stringency during different phases of the pandemic in the countries investigated.

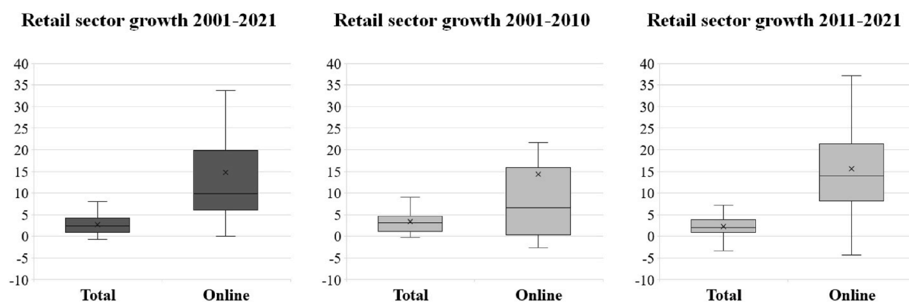

Fig. 8. Average annual growth rates in the retail sector in European countries (%).

to some extent the argument of the pandemic-induced upward boost of the online retail sector. Thus, while illuminating in other respects, this analysis, in itself, is unhelpful regarding the longer-term implications of the pandemic for the online retail sector. The next section aims to address this deficiency.

4.2. Long-term analysis (RQ2)

To investigate the potential trend-shifting impact of the pandemic in the online retail sector, a two-step approach is applied. First, to establish a basis for comparison, we analyze the 20-years trend of the sector without considering the specific effect of the pandemic. Second, based on the long-term trend established, we focus on the period of the pandemic, and use outlier detection methods to estimate whether the pandemic has induced a level shift in the long-term trend of the sector.

4.2.1. Long-term trend analysis

Online retail sales and online retail market shares show an increasing tendency during the last 20+ years (Fig. 3). While the retail sector as a whole had a slight increasing tendency during this period, the average annual growth rate of the online retail sector was clearly higher. This difference is most visible during the last ten years when the online retail sector has been constantly on an increasing trajectory, thereby raising its market share within the total retail sector. Thus, the online retail sector has been benefitting from continuous market share gains with a relatively lower growth pace in the early period (2001–2010), and with rapid increases in the last period (2011–2021). These differences are illustrated in Fig. 8.

Next, we use unit root tests to statistically demonstrate that there is an underlying long-term growth trend in the data (Chatfield and Xing, 2019), both in terms of monthly online retail turnover (*Online_Retail*) and in terms of online retail market share (*Online_Retail_Ratio*). Applying the most widely used Augmented Dickey-Fuller (ADF) test, we aim to show that there is a systematic, persistent stochastic trend in the time series (i.e., an upward tendency in our case). Unit root test results confirm that in most of the countries investigated the null hypothesis of one unit root cannot be rejected: the p-values are above 0.05 in 23 cases out of 24 in case of the *Online_Retail* variable and in 21 cases out of 24 for *Online_Retail_Ratio*. Thus, for the vast majority of countries neither *Online_Retail*, nor *Online_Retail_Ratio* is stationary, indicating that there is an (upward) long-term stochastic trend in the time series. Furthermore, unit root test results also imply that any positive or negative shock (such as the pandemic) during the period investigated has a persistent effect on the trend. Nevertheless, further investigation is needed to determine whether this shock applies for the pandemic period as well.

4.2.2. Outlier detection during the pandemic

Outlier detection is used to determine whether the pandemic has caused a level shift in the *Online_Retail*, and especially in the *Online_Retail_Ratio* time series. For this purpose, we use ARIMA[1] models with specific dummy regressors on both time series, implemented in JDemetra+ which is a proprietary software developed by the National Bank of Belgium in cooperation with the Deutsche Bundesbank and Eurostat. The software has been officially recommended since 2015 to the members of the European Statistical System and the European System of Central Banks as a tool for seasonal adjustment and other connected time series issues, such as outlier detection. In general, outliers are represented by abrupt changes in a time series caused by unexpected natural or socioeconomic effects, such as the pandemic. Three main types of outliers can be identified (Fig. 9): (a) additive outlier (AO), which changes the time series for one period only, returning to the original trend afterwards, (b) level shift (LS) that causes a permanent (upward or downward) change in the level of a time series, and (c) transitory change (TC) whose effect of changing the time series is faded out over a limited number of periods (IMF, 2018). Here, we specifically look for LS type outliers: a positive LS would suggest that online retail turnover and its market share registered a sudden increase during the pandemic, and that therefore the pandemic has accelerated the underlying growth trend of online retail.

[1] Autoregressive Integrated Moving Average.

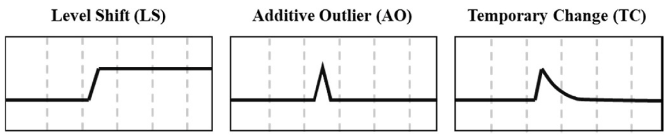

Fig. 9. Level shift versus other outlier types (source: IMF, 2018).

Table 4
Level shift (LS) detection during the pandemic.

	Online_Retail		Online_Retail_Ratio	
	LS date	Magnitude (t-value)	LS date	Magnitude (t-value)
Austria	04–2020	+.161 (6.573)	03–2020	+.149 (5.667)
Belgium	04–2020	+.266 (5.77)	–	–
Bulgaria	–	–	–	–
Czechia	–	–	03–2020	+.142 (12.52)
Germany	04–2020	+.214 (9.752)	–	–
Denmark	04–2020	+.206 (6.138)	03–2020	+.183 (4.902)
Estonia	–	–	–	–
Greece	–	–	–	–
Spain	04–2020	+.339 (8.350)	03–2020	+.201 (5.479)
Finland	04–2020	+.259 (10.479)	04–2020	+.259 (10.634)
France	05–2020	+.167 (10.036)	03–2020	+.151 (7.447)
Croatia	–	–	–	–
Hungary	–	–	–	–
Italy	05–2020	+.011 (1.837)	03–2020	+.247 (28.143)
	08–2020	+.020 (3.615)	06–2020	−.092 (−9.905)
			11–2020	+.117 (11.338)
Lithuania	04–2020	+90.59 (49.585)	11–2020	+25.291 (12.4)
	11–2020	+27.01 (13.700)		
Netherlands	04–2020	+.158 (6.298)	–	–
Norway	03–2020	+.215 (7.412)	03–2020	+.203 (7.08)
	11–2020	+.138 (4.863)	06–2020	−.112 (−3.904)
			11–2020	+.149 (5.543)
Poland	–	–	–	–
Portugal	–	–	–	–
Romania	–	–	–	–
Sweden	04–2020	+.180 (9.191)	04–2020	+.203 (10.393)
Turkey	–	–	–	–
United Kingdom	04–2020	+.170 (5.772)	04–2020	+.349 (12.074)
EU-27	04–2020	+.185 (12.005)	11–2020	+.131 (9.141)

JDemetra+ uses the traditional TRAMO[2] methodology (Gómez and Maravall, 1996; Findley et al., 2017) where TRAMO is designed to perform outlier detection as well.[3] Although this is a widely used framework in economics and connected disciplines, its applications in retailing are quite scarce which offers us the possibility to shed additional light on the effect of the pandemic on the online retail sector. In particular, TRAMO uses regression models with ARIMA errors as follows:

$$z_t = y_t\beta + x_t$$

where z_t is the original data series, $\beta = (\beta_1, \ldots \beta_n)$ is a vector of regression coefficients, $y_t = (y_{1t}, \ldots y_{nt})$ represents n regression variables (in our case LS, AO and TC outliers), while x_t is the disturbance that follows the general ARIMA process.

Using the TRAMO method, we analyze the full Jan 2000–Jan 2022 time period for outliers in each country involved in the analysis, complemented by the aggregated time series on the EU-27 level. Both *Online_Retail* and *Online_Retail_Ratio* time series were analyzed for all three types of outliers. However, in light of RQ2, only LS type outliers are listed in Table 4 that were identified during 2020. It should be noted that 2021 LS outliers are not (yet) taken into consideration here because they are situated at the end of our time series data (i.e., further data is needed by TRAMO to determine whether a 2021 LS will remain significant and persist in the long run). In contrast, LS outliers in 2020 have already proven that they induced a persistent upward shock into the long-term trend of the online retail sector. Table 4 lists all significant level shifts (p < .05) detected during 2020. Full results are presented in Appendix B.

The results of LS detection indicate that at the level of the EU-27, as well as in most of the countries investigated there was at least one positive LS in the online retail trend during the first year of the pandemic. This strongly suggests that COVID-19 has induced a boost both to online retail turnover and to its market share, supporting the window of opportunity concept. Out of the 23 countries analyzed, only 9 where had no significant LS. However, these cases represent smaller European countries, the largest ones (Germany, France, Italy, Spain, UK) all experiencing positive significant LSs. Furthermore, some of the countries (Italy, Lithuania, Norway) experienced multiple significant LSs during 2020 which further strengthens our conclusion related to the long-term implications of the pandemic. While there are two anomalous negative LSs in the *Online_Retail_Ratio* as well (Table 4), we suggest that these do not contradict our results, as these are all overcompensated by multiple positive LSs in the same countries (Italy and Norway), the magnitude of which is significantly higher than that of the negative LSs. Nevertheless, these negative LSs could be a sign of a significant "phase-out" effect, as discussed in the short-term analysis.

5. Summary and discussion

Two important gaps were addressed in this paper: (RQ1) how can factors related to consumer behavior (mobility) and regulations (government stringency) explain the volatile evolution of online retail sales during the pandemic, and (RQ2) what long-term trend-shifting effects can be identified during the pandemic in the evolution trajectory of online retail.

First, our results confirm that the two indicators proposed to estimate changes in consumer behavior (*Residential mobility*) and in government regulations (*Government stringency*) can significantly explain the hectic short-term evolution of the online retail sector during the pandemic. Released for the first time during the pandemic, these two indicators are significantly above and beyond the explanatory power of traditional variables used to predict online channel use in pre-pandemic periods. The more people are confined to residential areas, and the stricter government restrictions are, the more customers turn to online channels. These results offer empirical support to previous studies that proposed that changes in mobility (Shankar et al., 2021) and pandemic-related government regulations (Hwang et al., 2020) could provide a better measure to estimate changes in online sales.

Second, using these newly introduced variables, our study goes beyond demonstrating the simple linear relationship between these variables and online retail turnover, to describe in more detail how online shopping habits change during the pandemic. This is a novel approach compared to existing studies that simply argue that the pandemic is linked to the increased use of online channels (e.g., Chang and Meyerhoefer, 2021; Hwang et al., 2020; Eger et al., 2021). Using government stringency and mobility data, we offer a more nuanced understanding of *how* online shopping behavior evolves during the different stages of the pandemic, an issue currently hotly debated in the literature (Kirk and Rifkin, 2020; Guthrie et al., 2021; Schleper et al., 2021). Three different phases are distinguished in this paper: (1) a lure-in phase; (2) a temporary lock-in phase; and (3) a phase-out period. Furthermore, the same phases seem to repeat during different waves of the pandemic, starting with a strong lure-in phase, followed by a mix of lock-in and phase-out periods.

Third, using advanced outlier detection methods, we show that the faster growth trend that characterized online retail in the past decade has experienced a new positive level shift during 2020 in most of the

[2] Time series Regression with ARIMA noise, Missing values and Outliers.
[3] A comprehensive description of the procedure and its technical implementation in JDemetra+ is provided by Eurostat's website.

countries investigated. In only a couple of months during the pandemic, online retail has gained extra market share against offline retail that in normal circumstances would have probably taken several years. Thus, our empirical findings confirm the predictions of some researchers (e.g., Chang and Meyerhoefer, 2021; Tran, 2021), and actively address the questions posed by other researchers (e.g., Sheth, 2020; Guthrie et al., 2021), by establishing that the pandemic has indeed induced a persistent upward shift into the growth trajectory of online retail. These level shifts were especially visible in the larger economies of Europe. Thus, our results are concordant with several other studies that suggest that many firms managed to quickly overcome infrastructural challenges and build up the necessary online capacities (Guo et al., 2020; Beckers et al., 2021; Reardon et al., 2021), while customers will continue to use online retail channels more intensively in post-lockdown periods as well (Hobbs, 2020; Eger et al., 2021; Hall et al., 2021). Even if some customers return to traditional shopping channels (Hobbs, 2020; Sheth, 2020), our results indicate that for a large segment of customers the pandemic-induced shock outweighs the potential phase-out effect, shifting their long-term orientation towards online channels.

6. Conclusion

This paper analyzed short-term drivers (RQ1) and long-term implications of the pandemic (RQ2) in the online retail sector, relying on the MLP's socio-technical approach as a theoretical lens. COVID-19 is operationalized within the MLP as an exogeneous landscape event that induced a shock on the regime level. This shock opened a window of opportunity for online retail to exponentially grow and significantly increase its share against traditional retail channels.

6.1. Theoretical implications

Our research shows that during a window of opportunity created by a landscape event, forces within the socio-technical regime that shape the long-term trajectory of a technology change radically. Geels and Schot (2007) argue that strong landscape pressures (such as a pandemic) destabilize actual socio-technical regimes creating tensions that open windows of opportunity for technologies to emerge. Our short-term analysis related to RQ1 offers additional insights into how these regime tensions function. Panel regression results indicate that during unstable periods (when windows of opportunity are created by landscape pressures), certain sub-regimes take over the force that shapes technological transitions, while other sub-regimes become negligible. In our study, the policy regime (strict government restrictions) and the user preferences and market regime (reorientation of shopping behaviors due to reduced mobility) were responsible for creating the tension on the regime-level. Conversely, other sub-regimes on the same level, such as technological regimes (e.g., technical infrastructure used in online retail), science regime (e.g., technical knowledge used to operate online transactions), and socio-cultural regimes (e.g., distrust of certain segments of the population in online retail), had no significant impact on the way online retail was evolving. Thus, we propose that windows of opportunity are created when one or more particular regimes exert pressures that take over the place of other regimes in creating the forces that shape technological transitions. When a window of opportunity is open, these new forces remain dominant and might even alter other regimes.

Second, our long-term analysis suggests that COVID-19 can be regarded as a shock-type landscape development that creates tension in the current socio-technical regime to create a window of opportunity for online retail. Results of our long-term analysis suggest that the quasi-stable socio-technical regime of the last decades enabled a gradual and constant growth of online retail in Europe, attaining continuously increasing market shares throughout the years. However, as the pandemic generated a window of opportunity for this sector, online retail was able to capitalize on this opportunity in most countries, receiving a significant boost to its previous growth tendency.

Third, as a more general research implication for retail, our study demonstrates that high-frequency indicators that emerged during the pandemic, such as data on population mobility and on government stringency can be used to better assess fundamental socio-economic processes during crises. These two types of indicators provide a more complex, real-time assessment of ongoing socio-economic processes, making them more suitable to make predictions or explain phenomena in a volatile context.

6.2. Practical implications

Through demonstrating that mobility and government stringency has a positive impact on the evolution of online sales, we offer an important tool to retail practitioners to monitor and anticipate potential large variations in online demand. While mobile GPS data has already been used to track retail store traffic, our analysis suggests that tracking customer movements outside brick-and-mortar stores can also provide an anchor during volatile times. Such high-frequency, near-real-time data could become the primary input for managers to keep up with sudden pandemic-related developments, and potentially with post-pandemic shopping behavior changes as well.

Online retailers that have already capitalized on this pandemic should also take into consideration that a sudden pandemic-related growth in sales could be followed by a temporary lock-in phase. However, retailers should continue to work on keeping (newly acquired) customers, as a phase-out period might rapidly occur. Conversely, our long-term analysis, suggests that actors in the online retail sector should expect that, on average, the phase-out effect is outweighed by the pandemic-induced boost in online sales, creating much potential on the long-run for online retailers to capture the benefits of the positive level shift in the growth trajectory of the sector.

6.3. Limitations and further research

A first set of limitations is related to the nature of data employed in our study. While Eurostat provides the most reliable macroeconomic data, comparable across countries, on the evolution of the (online) retail sector, aspects of the data were not ideal. Several countries had missing data on the most recent values of the online retail turnover index, and some European countries (e.g., Switzerland) could not be involved in our study at all. While all largest retail markets have been included in our sample, results of the study can nevertheless not be universally generalized beyond the 23 countries involved in the analysis.

In respect of GPS-based mobility and government stringency data, we have shown that these variables are suitable to explain the large variations in online retail sales during the pandemic. However, whether and to what extent these data can be used to keep up with developments in the online retail sector beyond the pandemic remains unknown but represents a promising direction for future research.

Another set of limitations stems from the results described in this paper. While our outlier detection could empirically demonstrate the pandemic-induced level shift in the long-term evolution of the online sector, statistically significant shifts were not observed in all the countries investigated. It remains an important future research avenue to explain why some countries, including the largest European economies, experienced level shifts during the pandemic, while others have not.

Lastly, this paper focused on the evolution of the online retail sector, explaining its volatile evolution during the pandemic and demonstrating how the sector could take advantage of the window of opportunity created by COVID-19. Our results could provide a starting point for investigating other technologies and solutions, such as video conferencing, home delivery or VR-solutions, to evaluate whether and to what extent they have capitalized on pandemic-induced opportunities, thereby shaping how the "*new normal*" might look like in a post-pandemic world.

Data availability

Data will be made available on request.

Acknowledgement

This research was partially supported by the PN-III-P1-1.1-TE-2019-1773 research project for young independent research teams funded by UEFISCDI Romania.

Appendix A. – Correlation matrix

Correlation	Δ Online retail	Δ Unemployment	Δ Residential	Δ Residential (−1)	Δ Government stringency	Δ Government stringency (−1)
Δ Online retail	1.0000					
Δ Unemployment	0.0682	1.0000				
Δ Residential	0.3406*	−0.0775	1.0000			
Δ Residential (-1)	0.3662*	0.0739	0.3323*	1.0000		
Δ Government stringency	0.3696*	0.0510	0.8244*	0.4035*	1.0000	
Δ Government stringency (-1)	0.3583*	0.2004*	0.2426*	0.8226*	0.3692*	1.0000

*significant at the p < .001 level.

Appendix B. Complete results of outlier detection

Table 5
Outlier detection with TRAMO in the Online_Retail time series (Jan 2000–Jan 2022)

Country	OUT (1)	OUT (2)	OUT (3)	OUT (4)	OUT (5)	OUT (6)	OUT (7)	OUT (8)	OUT (9)	OUT (10)
EU-27	TC (7–2021): −0.114 [-6.265]	TC (7–2020): −0.105 [-6.765]	LS (4–2020): 0.185 [12.005]	LS (5–2015): 0.096 [6.315]	AO (8–2009): −0.059 [-3.58]	AO (12–2005): 0.061 [3.696]	AO (6–2000): −0.05 [-3.031]			
Belgium	LS (4–2020): 0.266 [5.77]	AO (11–2008): −0.313 [-6.097]	AO (7–2008): −0.46 [-9]	LS (1–2006): −0.54 [-11.719]	AO (5–2001): 0.501 [9.567]	AO (4–2001): 0.211 [4.054]				
Bulgaria	LS (1–2006): −0.269 [-4.574]									
Czechia	TC (4–2020): 0.19 [26.189]	TC (12–2019): 0.041 [5.591]	TC (8–2014): 0.136 [23.936]	LS (1–2013): 0.122 [19.92]	LS (12–2008): −0.144 [-23.536]	AO (5–2000): 0.454 [50.068]				
Denmark	LS (4–2020): 0.206 [6.138]	AO (5–2005): 0.155 [4.791]	AO (12–2004): −0.233 [-7.159]	AO (7–2004): 0.215 [6.429]	LS (1–2004): 0.218 [6.693]	AO (12–2001): 0.213 [6.548]	AO (8–2001): −0.195 [-5.809]	AO (7–2001): 0.253 [7.519]	AO (4–2001): 0.183 [5.625]	TC (2–2001): −0.299 [-8.764]
Germany	LS (7–2021): −0.149 [-6.325]	LS (4–2020): 0.214 [9.752]	LS (5–2015): 0.205 [10.089]	LS (1–2015): 0.05 [2.445]	AO (4–2008): 0.083 [3.917]	AO (9–2006): −0.096 [-4.46]	AO (12–2005): 0.114 [5.327]	AO (6–2000): −0.127 [-5.169]	AO (5–2000): 0.129 [5.24]	
Estonia	LS (1–2005): −0.391 [-4.776]	TC (8–2003): −0.308 [-3.892]	TC (8–2002): 0.31 [3.914]							
Greece	AO (7–2015): −0.386 [-4.014]	AO (8–2008): −0.429 [-4.46]	LS (12–2004): −0.502 [-4.008]							
Spain	AO (7–2021): −0.228 [-6.79]	AO (7–2020): −0.217 [-6.468]	LS (4–2020): 0.339 [8.35]	LS (5–2015): 0.225 [5.535]	LS (9–2012): −0.181 [-4.446]	AO (8–2001): 0.211 [6.289]	AO (2–2001): 0.401 [11.971]			
France	TC (7–2021): −0.092 [-4.605]	TC (2–2021): 0.123 [6.796]	AO (7–2020): −0.219 [-14.341]	LS (5–2020): 0.167 [10.036]	AO (4–2017): −0.064 [-4.179]	LS (8–2015): 0.157 [9.461]	AO (8–2009): −0.06 [-3.929]	AO (4–2006): 0.07 [4.553]	AO (4–2005): 0.072 [4.705]	AO (11–2003): −0.09 [-5.91]
Croatia	AO (8–2020): −0.251 [-4.267]	AO (3–2020): −0.246 [-4.195]	AO (8–2019): −0.329 [-5.61]	TC (10–2014): −0.372 [-6.038]	TC (8–2014): 0.506 [8.207]	AO (7–2005): −0.286 [-4.868]	AO (2–2004): 0.306 [5.172]	AO (12–2003): −0.271 [-4.57]	AO (8–2003): −0.289 [-4.903]	LS (5–2003): −0.247 [-4.195]
Italy	AO (5–2021): −0.173 [-19.32]	LS (8–2020): 0.02 [3.615]	LS (5–2020): 0.011 [1.837]	AO (12–2018): −0.143 [-28.913]	TC (1–2014): 0.154 [44.932]	AO (1–2010): 0.126 [33.284]				
Lithuania	LS (7–2021): −30.487 [-13.656]	TC (3–2021):	LS (2–2021):	TC (12–2020):	LS (11–2020): 27.01 [13.7]	TC (6–2020):	LS (4–2020):	TC (3–2020):	AO (11–2019):	AO (4–2018):

(*continued on next page*)

Table 5 (*continued*)

Country	OUT (1)	OUT (2)	OUT (3)	OUT (4)	OUT (5)	OUT (6)	OUT (7)	OUT (8)	OUT (9)	OUT (10)
		25.141 [14.866]	16.387 [7.689]	111.835 [58.71]		−14.646 [-8.642]	90.59 [49.585]	11.86 [6.659]	−14.275 [-12.237]	−9.764 [-8.765]
Hungary	TC (4–2020): 0.393 [10.824]	LS (7–2011): 0.197 [9.63]	AO (12–2007): 0.123 [5.93]	AO (9–2006): −0.026 [-1.293]	AO (1–2005): −0.041 [-2.035]	AO (8–2004): −0.078 [-3.728]	AO (12–2002): −0.147 [-5.766]			
Netherlands	TC (1–2021): 0.19 [6.623]	LS (4–2020): 0.158 [6.298]	TC (2–2005): 0.262 [9.231]	AO (12–2004): −0.162 [-5.848]	TC (9–2004): 0.216 [7.467]	TC (1–2004): 0.179 [6.556]	AO (8–2002): 0.162 [5.963]	TC (9–2001): 0.162 [5.904]	AO (10–2000): −0.144 [-5.064]	LS (4–2000): 0.156 [5.577]
Austria	TC (11–2020): 0.173 [5.619]	LS (4–2020): 0.161 [6.573]	AO (7–2005): −0.124 [-3.734]	TC (4–2004): 0.131 [4.318]						
Poland	LS (10–2013): −0.225 [-3.898]	LS (1–2010): 0.327 [5.663]	LS (1–2008): 0.44 [7.604]	LS (1–2006): 0.578 [10.001]	TC (6–2001): −0.253 [-4.441]	TC (10–2000): −0.266 [-4.664]				
Portugal	TC (5–2019): 0.321 [4.498]	LS (1–2005): −0.587 [-8.939]	TC (1–2001): 0.387 [5.425]							
Romania	TC (1–2008): −1.589 [-38.435]	LS (12–2005): 1.346 [29.719]	AO (6–2005): 0.738 [19.879]	AO (1–2005): −1.199 [-28.919]	TC (11–2004): 0.396 [8.765]	LS (7–2004): 0.617 [10.883]	AO (9–2003): −0.296 [-8.396]	LS (1–2002): 0.295 [5.523]	LS (1–2001): 0.678 [12.269]	LS (7–2000): −0.4 [-7.31]
Finland	LS (4–2020): 0.259 [10.479]									
Sweden	LS (4–2020): 0.18 [9.191]	AO (5–2019): −0.078 [-3.674]	LS (4–2018): −0.175 [-8.951]	LS (1–2018): −0.075 [-3.803]	TC (12–2013): 0.076 [3.688]	AO (4–2006): 0.089 [4.183]	AO (12–2003): −0.113 [-5.36]	AO (12–2002): −0.101 [-4.745]	AO (10–2002): 0.083 [3.908]	AO (6–2001): 0.103 [4.869]
Norway	LS (6–2021): −0.2 [-7.072]	LS (2–2021): 0.132 [4.606]	LS (11–2020): 0.138 [4.863]	AO (4–2020): 0.161 [5.189]	LS (3–2020): 0.215 [7.412]	TC (12–2018): −0.141 [-4.648]	AO (9–2004): 0.123 [4.133]	LS (6–2001): −0.123 [-4.405]		
United Kingdom	TC (5–2020): 0.147 [4.603]	LS (4–2020): 0.17 [5.772]	LS (12–2002): −0.139 [-5.252]	LS (2–2001): −0.178 [-6.737]						
Turkey	AO (11–2019): 0.143 [4.528]	AO (11–2018): 0.176 [5.586]	TC (2–2014): −0.207 [-5.546]							

Content of cells: (a) type of outlier: LS – level shift, TC – transitory change, AO – Additive outlier; (b) month of occurrence in parentheses; (c) magnitude of outlier [t-value].

Table 6
Outlier detection with TRAMO in the Online_Retail_Ratio time series (Jan 2000–Jan 2022)

Country	OUT (1)	OUT (2)	OUT (3)	OUT (4)	OUT (5)	OUT (6)	OUT (7)	OUT (8)	OUT (9)	OUT (10)
EU27	LS (6–2021): −0.11 [-7.671]	LS (11–2020): 0.131 [9.141]	AO (7–2020): −0.085 [-5.169]	TC (4–2020): 0.271 [16.049]	TC (3–2020): 0.108 [6.457]	LS (5–2015): 0.091 [6.435]	AO (8–2009): −0.057 [-3.524]	LS (1–2006): −0.052 [-3.712]	AO (6–2000): −0.041 [-2.538]	
EU28	LS (5–2015): 0.078 [6.023]	AO (12–2005): 0.052 [3.274]								
Euro Area 19	TC (7–2021): −0.127 [-6.924]	TC (1–2021): 0.07 [4.287]	LS (11–2020): 0.124 [7.876]	TC (4–2020): 0.275 [15.286]	TC (3–2020): 0.108 [6.041]	AO (7–2020): −0.096 [-5.481]	LS (5–2015): 0.103 [6.897]	AO (8–2009): −0.06 [-3.459]	LS (1–2006): −0.056 [-3.716]	
Belgium	TC (11–2020): 0.237 [4.546]	TC (4–2020): 0.359 [6.913]	AO (11–2008): −0.248 [-4.722]	AO (7–2008): −0.374 [-7.144]	LS (1–2006): −0.559 [-11.922]	AO (5–2001): 0.523 [9.812]	AO (4–2001): 0.231 [4.333]			
Bulgaria	LS (1–2021): −0.24 [-4.114]									
Czechia	LS (5–2021): −0.073 [-5.852]	AO (12–2020):	AO (5–2020):	AO (4–2020):	LS (3–2020): 0.142 [12.52]	TC (8–2014):	LS (1–2013): 0.111 [13.906]	LS (12–2008):	LS (1–2004): 0.045 [5.568]	AO (5–2000):

(*continued on next page*)

Table 6 (*continued*)

Country	OUT (1)	OUT (2)	OUT (3)	OUT (4)	OUT (5)	OUT (6)	OUT (7)	OUT (8)	OUT (9)	OUT (10)
		−0.09 [-7.459]	0.061 [6.656]	0.178 [18.193]		0.121 [16.184]		−0.151 [-18.944]		0.452 [44.191]
Denmark	LS (3–2021): −0.161 [-4.311]	LS (3–2020): 0.183 [4.902]	AO (12–2004): −0.231 [-4.983]	LS (1–2004): 0.194 [5.204]	AO (12–2001): 0.182 [3.912]	AO (8–2001): −0.192 [-4.08]	AO (7–2001): 0.253 [5.387]	TC (2–2001): −0.272 [-6.217]		
Germany	TC (1–2021): 0.194 [7.337]	TC (4–2020): 0.265 [10.23]	LS (5–2015): 0.196 [8.446]	AO (12–2005): 0.099 [3.894]	AO (6–2000): −0.123 [-4.484]	AO (5–2000): 0.112 [4.074]				
Estonia	TC (4–2020): 0.374 [4.984]	LS (1–2005): −0.381 [-5.052]	TC (8–2003): −0.306 [-4.088]	LS (4–2001): 0.291 [3.859]						
Greece	LS (12–2004): −0.546 [-4.184]									
Spain	AO (9–2021): −0.181 [-4.587]	AO (7–2021): −0.255 [-7.796]	AO (7–2020): −0.198 [-6.431]	TC (4–2020): 0.519 [14.508]	LS (3–2020): 0.201 [5.479]	LS (5–2015): 0.219 [6.275]	AO (8–2001): 0.183 [6.349]	AO (2–2001): 0.382 [13.215]		
France	LS (6–2021): −0.141 [-7.295]	LS (2–2021): 0.1 [5.292]	AO (11–2020): 0.206 [10.403]	TC (7–2020): −0.214 [-10.419]	TC (4–2020): 0.172 [7.808]	LS (3–2020): 0.151 [7.447]	LS (8–2015): 0.157 [8.545]	AO (4–2005): 0.082 [4.25]		
Croatia	AO (4–2020): 0.409 [6.357]	AO (8–2019): −0.322 [-4.998]	TC (10–2014): −0.366 [-5.359]	TC (8–2014): 0.48 [7.019]	AO (7–2005): −0.275 [-4.266]	AO (2–2004): 0.315 [4.891]	AO (12–2003): −0.25 [-3.882]	AO (8–2003): −0.315 [-4.896]		
Italy	AO (5–2021): −0.192 [-17.094]	AO (1–2021): 0.048 [4.718]	LS (11–2020): 0.117 [11.338]	LS (6–2020): −0.092 [-9.905]	AO (4–2020): 0.114 [12.281]	LS (3–2020): 0.247 [28.143]	TC (5–2019): −0.032 [-4.527]	AO (12–2018): −0.135 [-19.603]	TC (1–2014): 0.157 [29.273]	AO (1–2010): 0.128 [21.782]
Lithuania	AO (3–2021): 8.777 [5.57]	TC (1–2021): 27.845 [16.032]	TC (12–2020): 106.929 [58.167]	LS (11–2020): 25.291 [12.4]	TC (6–2020): −10.686 [-5.922]	TC (5–2020): −25.697 [-15.036]	TC (4–2020): 105.011 [58.766]	TC (3–2020): 27.288 [15.714]	AO (11–2019): −12.908 [-8.995]	TC (4–2018): −8.16 [-5.004]
Hungary	TC (4–2020): 0.543 [14.62]	LS (7–2011): 0.206 [8.35]	LS (1–2008): −0.123 [-4.806]	AO (8–2006): 0.082 [3.077]	AO (11–2004): −0.142 [-6.156]	AO (8–2004): −0.16 [-5.844]	AO (10–2003): −0.108 [-4.615]	AO (12–2002): −0.167 [-6.749]		
Netherlands	TC (1–2021): 0.292 [7.055]	TC (4–2020): 0.181 [4.419]	TC (2–2005): 0.237 [5.78]	AO (9–2004): 0.186 [5.309]	AO (8–2002): 0.183 [5.22]	AO (9–2001): 0.152 [4.305]				
Austria	AO (1–2021): 0.184 [5.52]	TC (11–2020): 0.267 [8.561]	AO (4–2020): 0.284 [8.321]	LS (3–2020): 0.149 [5.667]						
Poland	TC (4–2020): 0.254 [4.295]	LS (1–2010): 0.295 [4.886]	LS (1–2008): 0.445 [7.39]	LS (1–2006): 0.546 [9.054]	AO (5–2001): 0.227 [4.415]	TC (10–2000): −0.267 [-4.521]				
Portugal	TC (12–2020): 0.259 [3.738]	AO (5–2019): 0.243 [4.099]	AO (4–2005): −0.228 [-3.844]	LS (1–2005): −0.692 [-11.59]	TC (1–2001): 0.384 [5.606]					
Romania	TC (1–2008): −1.624 [-37.838]	LS (12–2005): 1.27 [26.899]	AO (6–2005): 0.69 [17.072]	AO (1–2005): −1.133 [-27.327]	LS (7–2004): 0.448 [7.743]	LS (2–2002): 0.462 [9.506]	LS (1–2001): 0.679 [14.441]	LS (7–2000): −0.38 [-6.528]	AO (5–2000): −0.402 [-7.998]	AO (2–2000): −0.427 [-7.646]
Finland	LS (4–2020): 0.259 [10.634]									
Sweden	LS (4–2020): 0.203 [10.393]	TC (4–2019): −0.077 [-3.712]	LS (4–2018): −0.182 [-9.294]	AO (12–2013): 0.083 [4.165]	AO (4–2006): 0.106 [5.175]	TC (2–2006): −0.087 [-4.303]	AO (12–2003): −0.099 [-4.77]	AO (12–2002): −0.104 [-5.003]	AO (10–2002): 0.085 [4.255]	AO (6–2001): 0.116 [5.773]
Norway	LS (6–2021): −0.203 [-7.624]	LS (2–2021): 0.146 [5.378]	LS (11–2020): 0.149 [5.543]	LS (6–2020): −0.112 [-3.904]	AO (4–2020): 0.138 [4.22]	LS (3–2020): 0.203 [7.08]	TC (12–2018): −0.131 [-4.498]	AO (9–2004): 0.116 [3.93]	LS (6–2001): −0.139 [-5.283]	
United Kingdom	LS (4–2020): 0.349 [12.074]	TC (3–2020):	LS (12–2002):	LS (2–2001): −0.204 [-7.186]	TC (1–2001):					

(*continued on next page*)

Table 6 (*continued*)

Country	OUT (1)	OUT (2)	OUT (3)	OUT (4)	OUT (5)	OUT (6)	OUT (7)	OUT (8)	OUT (9)	OUT (10)
		0.129 [4.453]	−0.133 [-4.705]		−0.113 [-3.931]					
Turkey	AO (5–2021): 0.124 [3.641]	TC (4–2020): 0.343 [8.118]	AO (11–2019): 0.141 [4.16]	AO (11–2018): 0.183 [5.392]	TC (2–2014): −0.166 [-3.94]					

Content of cells: (a) type of outlier: LS – level shift, TC – transitory change, AO – Additive outlier; (b) month of occurrence in parentheses; (c) magnitude of outlier [t-value].

References

Beckers, J., Weekx, S., Beutels, P., Verhetsel, A., 2021. COVID-19 and retail: the catalyst for e-commerce in Belgium? J. Retailing Consum. Serv. 62, 102645.

Chang, H.H., Meyerhoefer, C.D., 2021. COVID-19 and the demand for online food shopping services: empirical Evidence from Taiwan. Am. J. Agric. Econ. 103 (2), 448–465.

Chatfield, C., Xing, H., 2019. The Analysis of Time Series: an Introduction with R. Chapman and hall/CRC.

Chopdar, P.K., Paul, J., Prodanova, J., 2022. Mobile shoppers' response to Covid-19 phobia, pessimism and smartphone addiction: does social influence matter? Technol. Forecast. Soc. Change 174, 121249.

Dannenberg, P., Fuchs, M., Riedler, T., Wiedemann, C., 2020. Digital transition by COVID-19 pandemic? The German food online retail. Tijdschr. Econ. Soc. Geogr. 111 (3), 543–560.

Eger, L., Komárková, L., Egerová, D., Mičík, M., 2021. The effect of COVID-19 on consumer shopping behaviour: generational cohort perspective. J. Retailing Consum. Serv. 61, 102542.

Findley, D.F., Lytras, D.P., McElroy, T.S., 2017. Detecting seasonality in seasonally adjusted monthly time series. Statistics 3.

Gao, X., Shi, X., Guo, H., Liu, Y., 2020. To buy or not buy food online: the impact of the COVID-19 epidemic on the adoption of e-commerce in China. PLoS One 15 (8), e0237900.

Gauri, D.K., Jindal, R.P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., Navallo, J.R., Fogarty, J., Carr, S., Howerton, E., 2021. Evolution of retail formats: past, present, and future. J. Retailing 97 (1), 42–61.

Geels, F.W., 2002. Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. Res. Pol. 31 (8–9), 1257–1274.

Geels, F.W., 2004. From sectoral systems of innovation to socio-technical systems: insights about dynamics and change from sociology and institutional theory. Res. Pol. 33 (6–7), 897–920.

Geels, F.W., 2011. The multi-level perspective on sustainability transitions: responses to seven criticisms. Environ. Innov. Soc. Transit. 1 (1), 24–40.

Geels, F.W., Schot, J., 2007. Typology of sociotechnical transition pathways. Res. Pol. 36 (3), 399–417.

Genus, A., Coles, A.M., 2008. Rethinking the multi-level perspective of technological transitions. Res. Pol. 37 (9), 1436–1445.

Gómez, V., Maravall, A., 1996. Programs TRAMO and SEATS: Instructions for the User (Beta Version: September 1996). Banco de España. Servicio de Estudios.

Google, L.L.C., 2021. Google COVID-19 Community Mobility Reports. https://www.google.com/covid19/mobility/. (Accessed 31 October 2021).

Guo, H., Liu, Y., Shi, X., Chen, K.Z., 2020. The role of e-commerce in the urban food system under COVID-19: lessons from China. China Agric. Econ. Rev. 13 (2), 436–455.

Guthrie, C., Fosso-Wamba, S., Arnaud, J.B., 2021. Online consumer resilience during a pandemic: an exploratory study of e-commerce behavior before, during and after a COVID-19 lockdown. J. Retailing Consum. Serv. 61, 102570.

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., et al., 2021. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nat. Human Behav. 5 (4), 529–538.

Hall, M.C., Prayag, G., Fieger, P., Dyason, D., 2021. Beyond panic buying: consumption displacement and COVID-19. J. Serv. Manag. 32 (1), 113–128.

Hao, N., Wang, H., Zhou, Q., 2020. The impact of online grocery shopping on stockpile behavior in Covid-19. China Agric. Econ. Rev. 12 (3), 459–470.

Helm, S., Kim, S.H., Van Riper, S., 2020. Navigating the 'retail apocalypse': a framework of consumer evaluations of the new retail landscape. J. Retailing Consum. Serv. 54, 101683.

Hobbs, J.E., 2020. Food supply chains during the COVID-19 pandemic. Can. J. Agric. Econ. 68 (2), 171–176. https://doi.org/10.1111/cjag.12237.

Hortaçsu, A., Syverson, C., 2015. The ongoing evolution of US retail: a format tug-of-war. J. Econ. Perspect. 29 (4), 89–112.

Hwang, E., Nageswaran, L., Cho, S., 2020. Impact of COVID-19 on Omnichannel Retail: Drivers of Online Sales during Pandemic. SSRN 3657827.

IMF, 2018. *Quarterly National Accounts Manual*. International Monetary Fund. Statistics Department.

Jiang, Y., Stylos, N., 2021. Triggers of consumers' enhanced digital engagement and the role of digital technologies in transforming the retail ecosystem during COVID-19 pandemic. Technol. Forecast. Soc. Change 172, 121029.

Jílková, P., Králová, P., 2021. Digital consumer behaviour and eCommerce trends during the COVID-19 crisis. Int. Adv. Econ. Res. 1–3.

Kirk, C.P., Rifkin, L.S., 2020. I'll trade you diamonds for toilet paper: consumer reacting, coping and adapting behaviors in the COVID-19 pandemic. J. Bus. Res. 117, 124–131.

Li, J., Hallsworth, A.G., Coca-Stefaniak, J.A., 2020. Changing grocery shopping behaviours among Chinese consumers at the outset of the COVID-19 outbreak. Tijdschr. Econ. Soc. Geogr. 111 (3), 574–583.

Lund, S., Madgavkar, A., Manyika, J., Smit, S., Ellingrud, K., Meaney, M., Robinson, O., 2021. The Future of Work after COVID-19. McKinsey Global Institute.

Martin-Neuninger, R., Ruby, M.B., 2020. What does food retail research tell us about the implications of coronavirus (COVID-19) for grocery purchasing habits? Front. Psychol. 11, 1448 https://doi.org/10.3389/fpsyg.2020.01448.

Mehrolia, S., Alagarsamy, S., Solaikutty, V.M., 2021. Customers response to online food delivery services during COVID-19 outbreak using binary logistic regression. Int. J. Consum. Stud. 45 (3), 396–408.

Pantano, E., Pizzi, G., Scarpi, D., Dennis, C., 2020. Competing during a pandemic? Retailers' ups and downs during the COVID-19 outbreak. J. Bus. Res. 116, 209–213.

Reardon, T., Heiman, A., Lu, L., Nuthalapati, C.S., Vos, R., Zilberman, D., 2021. "Pivoting" by food industry firms to cope with COVID-19 in developing regions: e-commerce and "copivoting" delivery intermediaries. Agric. Econ. 52 (3), 459–475. https://doi.org/10.1111/agec.12631.

Roggeveen, A.L., Sethuraman, R., 2020. How the COVID-19 pandemic may change the world of retailing. J. Retailing 96 (2), 169–171.

Schleper, M.C., Gold, S., Trautrims, A., Baldock, D., 2021. Pandemic-induced knowledge gaps in operations and supply chain management: COVID-19's impacts on retailing. Int. J. Oper. Prod. Manag. 41 (3), 193–205.

Shankar, V., Kalyanam, K., Setia, P., Golmohammadi, A., Tirunillai, S., Douglass, T., Hennessey, J., Bull, J.S., Waddoups, R., 2021. How technology is changing retail. J. Retailing 97 (1), 13–27.

Sheth, J., 2020. Impact of Covid-19 on consumer behavior: will the old habits return or die? J. Bus. Res. 117, 280–283.

Sneader, K., Singhal, S., 2021. The Next Normal Arrives: Trends that Will Define 2021-and beyond. McKinsey and Company.

Tran, L.T.T., 2021. Managing the effectiveness of e-commerce platforms in a pandemic. J. Retailing Consum. Serv. 58, 102287 https://doi.org/10.1016/j.jretconser.2020.102287.